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LS-SVM Combined with ZNN for Predicting the Continuous Motion Joint Angle of Lower Limb

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Abstract: In this paper, a method fusing least squares support vector machine (LS-SVM) with Gaussian kernel function and zeroing neural network (ZNN) is proposed to forecast the continuous motion of lower limb. The surface electromyography (sEMG) signal contains human behavior information and directly reflects the movement intention. In the experiment, the sEMG signal of the lower limbs when the tester is doing leg extension exercise is collected and the real knee joint angle is recorded at the same time. Then the raw sEMG is subjected to a series of preprocessing, and the corresponding muscle activation is gained by calculation. The muscle activation is used as input to the LS-SVM model, and the output to the model is the knee joint angle. LS-SVM transforms the original problem into solving linear equations. When the amount of data is relatively large, the traditional solution method is very time-consuming, and the proposed ZNN method is able to solve the problem, thus speeding up the convergence speed and greatly reducing the learning time. Finally, the back propagation neural network (BPNN) model is utilized to form a comparative experiment. The numerical results indicate that a more stable and better performance is reflected in the raised method, which provides a valuable reference for the research of joint continuous estimation.

Key Words: sEMG, LS-SVM, ZNN, Joint angle estimation, BPNN

1 Introduction

The evolution of robotics technology is particularly rapid, and its applications have spread across many fields, such as military, medical and service industries [1, 2]. Among them, robots for rehabilitation are very popular research fields in recent years, for instance, intelligent prostheses [3, 4] and exoskeleton robots [5]. According to the theory of rehabilitation medicine, the rehabilitation training method combined with active recognition of human movement intention has a very positive effect on the recovery of patients. Therefore, it is very meaningful to accurately obtain the human movement intention in real time. Compared with the traditional program-controlled human-machine interaction method, modern robots can actively understand the way of human movement, have the ability to adapt independently, and realize the direct combination of robot and human. Bioelectric signals serve as a bridge for information exchange. The widely used bioelectric signals include electromyographic signals, brain electrical signals, and eye electrical signals [6].

Understanding human behavior by decoding the information contained in EMG signals is a common method of intention recognition. Compared with other signals, the EMG signal acquisition technology is relatively mature and non-invasive.The essence of EMG signal is a kind of potential difference produced by muscle contraction, which can occur in any tissue organ. The sEMG signal is a sequence of electric potentials released by many motor units, superimposed on the surface of the skin with a comprehensive result of time and space [7]. The sEMG signal is a very feeble electrical signal, and its amplitude is usually proportional to the strength of muscle contraction. In particular, sEMG signal is generally generated 30∼150 ms ahead of the actual limb movement [7]. This feature lays the foundation for the prediction of movement intention. Since the sEMG signal contains the command information of the neuromuscular system in real time, the technology of using sEMG to realize human-machine interaction has become the object of many researchers [8–10].

At present, the method of intention recognition is roughly divided into two categories. One is the classification of limb movements and the recognition of movement patterns [11], and the other is the estimation of continuous joint movement [12]. For action classification, the methods are more mature, and the most important link is the feature extraction [13] of sEMG signals and the structure of classification models. The commonly used models for solving classification problems are K-nearest neighbor (KNN) [14], multilayer perceptron (MLP) [15] and artificial neural network (ANN) [16]. Qin et al. [17] used the Gaussian kernel linear discriminant analysis (GK-LDA) with wilson amplitude (WAMP) to classify four sport modes of the lower limbs. The recognition accuracy was as high as 96%. Vimal et al. [18] utilized wavelet packet transform to extract features of the sEMG signal, and the proposed region-convolutional neural network (R-CNN) method to accurately recognize gesture actions with an accuracy of 96.48%. For joint continuous motion estimation, there are generally two research methods. One is to establish a dynamic model between sEMG and joint angles by combining muscle physiology and the the most commonly utilized model to estimate joint motion is Hill model [19]. The other is to directly establish the functional relationship

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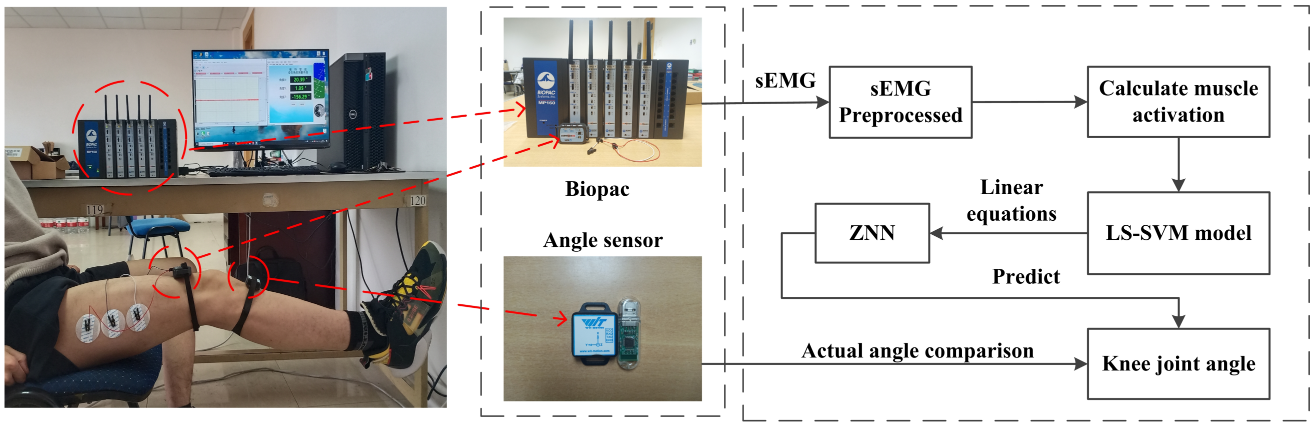

Fig. 1: The experimental process of motion intention recognition

between sEMG and joint movement. Ma et al. [20] took a short connected autoencoder long short-term memory (SCA-LSTM) model to complete the prediction of the continuous motion angle of the shoulder and elbow joints. Zhang et al. [21] applied the BPNN model for estimating the joint angles of the lower limbs of healthy subjects and patients. Neural network is used as a common method of intention recognition and has achieved good results.

In this paper, a method based on least squares support vector machine (LS-SVM) [22] combined with zeroing neural network (ZNN) [23–25] is proposed to predict the lower limb knee joint angle. LS-SVM is an improved algorithm of SVM. SVM is a supervised machine learning method that uses structural risk minimization criteria. The essence of SVM is a quadratic programming problem with unequal constraints, and its objective function is a convex quadratic function. In contrast to the traditional neural network, SVM can theoretically obtain the global optimal solution. SVM is a more stable algorithm whose structure is determined only by support vectors, while neural networks need repeated attempts to determine the network structure, and the output of neural networks is random. LS-SVM transforms inequality constraints into equality constraints, thereby simplifying the original problem into a problem of solving linear equations [22]. When the dimensionality of the equations is huge, the traditional solving method is very time-consuming and the memory usage is large. A zeroing neural network which can be called a special recurrent neural network is exploited to solve this problem, which effectively improves the convergence speed and reduces the calculation time.

The remaining in the paper can be expressed as follows: In Section 2, the data collection and processing operation is described. The Section 3 describes the derivation and establishment of the model. The experimental results of simulation by MATLAB are given in Section 4. In the end, the conclusion is shown in Section 5.

2 Methodology

2.1 Signal acquisition

In this experiment, a set of healthy individual data was actually adopted to give a method of motion estimation, which lays the foundation for subsequent rehabilitation intention recognition. The sEMG signal will vary with different individuals. When the data is processed by the learning algorithm, a part of the data is selected for training to obtain model parameters, and the other part is used as test data to observe the prediction effect of the model. Therefore, the differences in data between different healthy individuals and different sampling locations will not significantly affect the learning effect.

During the experiment, the sEMG signal of vastus lateralis muscle (VL) is sampled. Because after calculation and analysis, compared with other muscles, there is a strong linear correlation toward the sEMG signal of VL and the knee joint angle. The sEMG signal is acquired by Biopac system which is a wireless physiological data acquisition and analysis system. The device can record multi-channel EMG signals at the same time, and the sampling frequency of each channel is 2000 Hz. Knee joint angle is obtained by an angle sensor with a sampling frequency of 100 Hz to provide real joint motion data for reference.

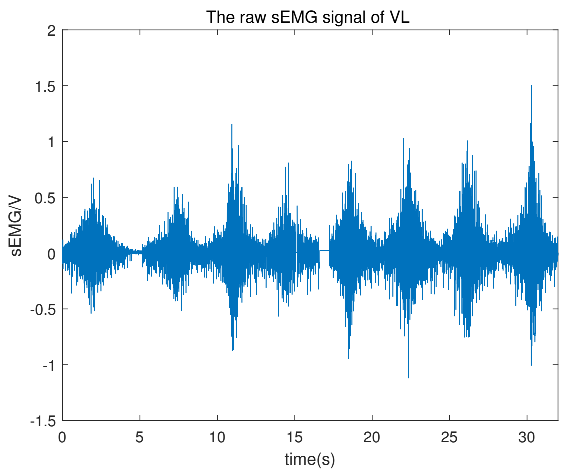

Fig. 2: The raw sEMG signal

In this paper, a healthy adult male tester is selected to perform continuous leg extension exercise. Furthermore, there is no obvious difference between the left leg and the right leg of the same person, but the muscle strength is different, thus the sEMG signal will be different. The movement trend of the leg starts from the knee joint perpendicular to the ground and ends parallel to the ground, completing the maximum contraction of the muscles. The entire experimental process of motion intention recognition and equipments for obtaining data are described in Figure 1. Because sEMG signal is easily disturbed from environmental noise, the surface of the skin should be cleaned before collecting the signal, then select the appropriate muscle and surface electrode placement point. Finally, through the experiment, the raw sEMG signal of VL and the real knee joint angle are shown in Figure 2 and Figure 3.

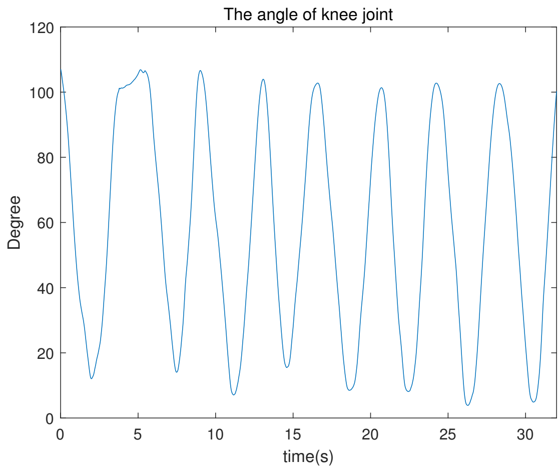

Fig. 3: The recorded Knee joint angle

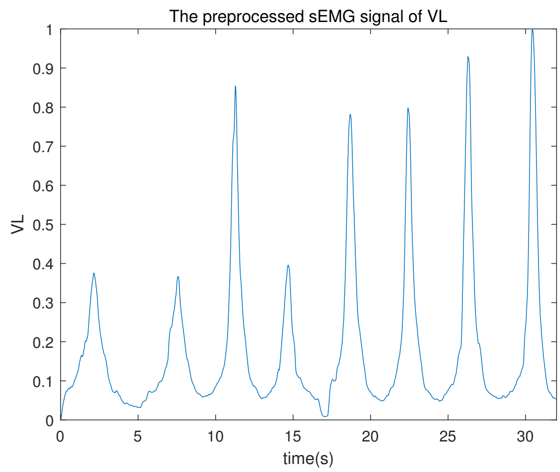

Fig. 4: The sEMG signal after preprocessing

2.2 Signal processing

The sEMG signal collected by Biopac system is a weak signal with low signal to noise ratio. It not only contains sEMG signal, but also noise generated by other physiological factors, power frequency interference, DC baseline noise, etc. For the lower limbs, the interference is more intense. Therefore, the raw sEMG signal cannot be used directly, and it must be further denoised. In the research, a 50 Hz notch filter, a band-pass filter(the low cut-off frequency is 20 Hz and the high cut-off frequency is 375 Hz), and full-wave rectification are applied to the raw sEMG signal.

The sEMG signal that has undergone preliminary denoising requires further processing. The preprocessed sEMG signal of VL is shown in Figure 4. From the above experiment, the frequency of collecting sEMG signal is not consistent with the angle sensor. In order to match the two signal more closely, the sEMG signal needs to be performed sub-sampling processing. The process is represented as

$$\mathrm{sEMG}(n) = \frac{1}{N} \sum_{i=nN-N+1}^{nN} \mathrm{sEMG}(i) \tag{1}$$

where N is the sub-sampling interval of signals, sEMG(n) is an average value of the sEMG signal. Because the frequency of acquiring the sEMG signal is 2000 Hz while the angle sensor is 100 Hz, they are 20 times different. In this paper, the number of N=20 is used. The sampling frequency after preprocessing is altered from 2000 Hz to 100 Hz. Through the step, the goal of making the frequencies of the two signals consistent is achieved.

2.3 Muscle activation acquisition

The sEMG signal can reflect the movement intention of human, and is related to the muscle strength. When using the sEMG to predict the continuous motion of the joint, the muscle activation is usually extracted from the sEMG signal first. Muscle activation is a better reflection of muscle contraction. There are many ways to calculate muscle activation. In the paper, the nonlinear mapping model of muscle activation is as follows:

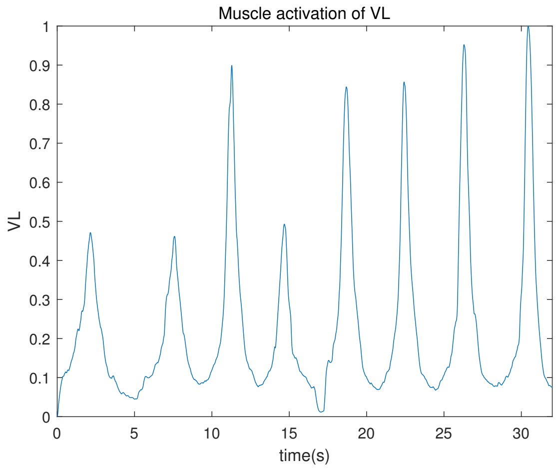

Fig. 5: Muscle activation

$$c_j(i) = \frac{e^{A_j} \cdot u_j(i) - 1}{e^{A_j} - 1} \tag{2}$$

where $c_j(i)$ is the muscle activation of the jth channel, A_j is the nonlinear shape coefficient representing the degree of nonlinearity between the sEMG signal and the muscle activation, $u_j(i)$ is the normalized sEMG of the jth channel after preprocessing, which can be expressed as:

$$u_j(i) = \frac{\mathrm{sEMG}_j(i) - \min(\mathrm{sEMG}_j(i))}{\max(\mathrm{sEMG}_j(i)) - \min(\mathrm{sEMG}_j(i))} \tag{3}$$

where $\min(\mathrm{sEMG}_j(i))$ and $\max(\mathrm{sEMG}_j(i))$ respectively describe the minimum and maximum values of the jth channel sEMG signal.

The parameter A_j usually ranges from -3 to 0. When $A_j = 0$, it represents a linear relationship. In this article, $A_j = 0.8$ is adopted. The muscle activation of VL calculated by the sEMG signal is shown in Figure 5.

3 Model Establishment

3.1 LS-SVM Model

In this experiment, a method based on LS-SVM combined with ZNN is raised to forecast the motion of knee joint. For regression problems, LS-SVM fits the known data by finding an optimal hyperplane. The optimal hyperplane represents the functional relation among the input x (muscle activation) and the output y (knee joint angle), which can be indicated as follows

$$y = \lambda^T \psi(x) + q \tag{4}$$

where $\psi(x)$ express a function that transforms sample data from low dimensional space to high dimensional space. This process makes the above issue into the linear case.

LS-SVM is able to express as a quadratic programming problem with equality constraints as described below. Error is also one of the optimal goals, and the error variable is defined as τ.

$$\begin{aligned} \min T(\lambda, q, \tau) &= \frac{1}{2}\lambda^T\lambda + \frac{1}{2}C\sum_{i=1}^{M}\tau_i^2 \\ s.t. \quad y_i &= \lambda^T\psi(x_i) + q + \tau_i \end{aligned} \tag{5}$$

where $i = 1 \cdots M$ represents the amount of training samples, the weight vector is described by λ, q is the offset, and C is an adjustable parameter to balance the search for the optimal hyperplane and the smallest deviation.

Using Lagrange multiplier method to transform the original problem into a single parameter. The process can be introduced as

$$L(\lambda, q, \tau, \xi) = T(\lambda, q, \tau) - \sum_{i=1}^{M}\xi_i(\lambda^T\psi(x_i) + q + \tau_i - y_i) \tag{6}$$

where ξ_i express the Lagrange multipliers.

In the light of the Karush-Kuhn-Tucker (KKT) condition, the necessary condition for taking the minimum value is that the derivative of the function L for the unknown variable λ, q, τ, ξ is 0. It can be expressed as

$$\begin{cases} \frac{\partial L}{\partial \lambda} = 0 \rightarrow \lambda = \sum_{i=1}^{M}\xi_i\psi(x_i) \\ \frac{\partial L}{\partial q} = 0 \rightarrow \sum_{i=1}^{M}\xi_i = 0 \\ \frac{\partial L}{\partial \tau} = 0 \rightarrow \xi_i = C\tau_i \\ \frac{\partial L}{\partial \xi} = 0 \rightarrow \lambda^T\psi(x_i) + q + \tau_i - y_i = 0 \end{cases} \tag{7}$$

where $i = 1, 2, \cdots M$ also represents the quantity of selected training samples.

Because the operation of inner product is involved in the solution process, if the sample mapping ψ is calculated first, and then calculate the inner product, the complexity is quite high. When the sample is mapped into a very high-dimensional space, it will bring a very heavy storage and calculation burden. So it is necessary to introduce the technology of the kernel function. The basic idea of the kernel technique is to simplify two operations of sample mapping and inner product into one step, thereby greatly reducing the computational complexity. In the paper, Gaussian kernel function possessing parameter σ^2 is applied, expressed as the following formula.

$$K(x_i, x_j) = \exp(\frac{-\| x_i - x_j \|^2}{2\sigma^2}) \tag{8}$$

Therefore, the above problem is transformed into solving the linear equations as the following Eq.(9), where the kernel function can be defined as follows:

$$\begin{bmatrix} 0 & 1 & \cdots & 1 \\ 1 & K(x_i, x_j) + \frac{1}{C} & \cdots & K(x_i, x_j) \\ \vdots & \vdots & \ddots & \vdots \\ 1 & K(x_i, x_j) & \cdots & K(x_i, x_j) + \frac{1}{C} \end{bmatrix} \begin{bmatrix} q \\ \xi_1 \\ \vdots \\ \xi_M \end{bmatrix} = \begin{bmatrix} 0 \\ y_1 \\ \vdots \\ y_M \end{bmatrix} \tag{9}$$

where $K(x_i, x_j) = \psi(x_i)^T\psi(x_j)$.

The above-mentioned equations are expressed in the form shown as the following formula (10).

$$Y(t)n(t) = z(t) \tag{10}$$

where $Y(t)$ represents a matrix with time-varying parameters, $n(t)$ and $z(t)$ are vectors that change with time. ZNN is a new type of recurrent neural network that solves time-varying quadratic programming problems with equality constraints by solving equations.

The same as the process of solving LS-SVM above, using the Lagrange multiplier method and setting its derivative to the optimization variable to zero to obtain the equations as represented by Eq.(10). Therefore, the proposed ZNN can be applied to problem solving. The following describes the establishment of the ZNN model.

3.2 ZNN Model

The core of ZNN design is to ensure that every component of the error function converges to 0. The definition of the deviation function is expressed as follows

$$e(t) = Y(t)n(t) - z(t) \tag{11}$$

In order to make $e(t)$ to be 0, the design formula of ZNN is described as:

$$\dot{e}(t) = -\gamma e(t) \tag{12}$$

where the parameter γ represents the convergence rate of ZNN. Combining formulas (11) and (12), a model for settling the time-varying quadratic programming problem is able to gain.

$$Y(t)\dot{n}(t) = -\dot{Y}(t)n(t) - \gamma(Y(t)n(t) - z(t)) + \dot{z}(t) \tag{13}$$

In fact, what LS-SVM describes is a static quadratic programming problem, while ZNN is designed for time-varying quadratic programming. Therefore, the obtained model cannot be used directly. In this case, the coefficient matrix in Eq.(9) needs to be regarded as a time-varying constant matrix. Finally, after further deduction, the ZNN model of dynamic solution process is presented as follows

$$Y(t)\dot{n}(t) = -\gamma(Y(t)n(t) - z(t)) \tag{14}$$

The obtained model of ZNN is used to settle the linear equations represented by Eq.(9), and the parameters ξ and q are calculated. The regression function as to the muscle activation of VL and the joint angle is derived as

$$y = \sum_{i=1}^{M}\xi_i K(x_i, x_j) + q \tag{15}$$

4 Experimental Results

In the experiment, the proposed method of LS-SVM combining with ZNN is utilized to complete the estimation for the knee joint angle. Owing to the content in second section, the experimental data is collected by the tester doing leg extension exercises and the motion lasts for 32 seconds.

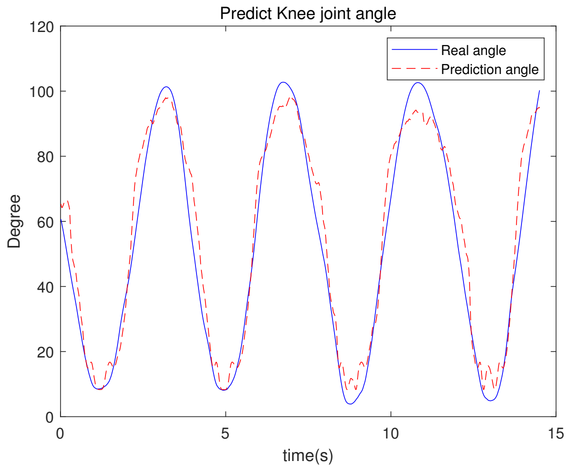

Fig. 6: The case where the C=1 and σ^2=0.2

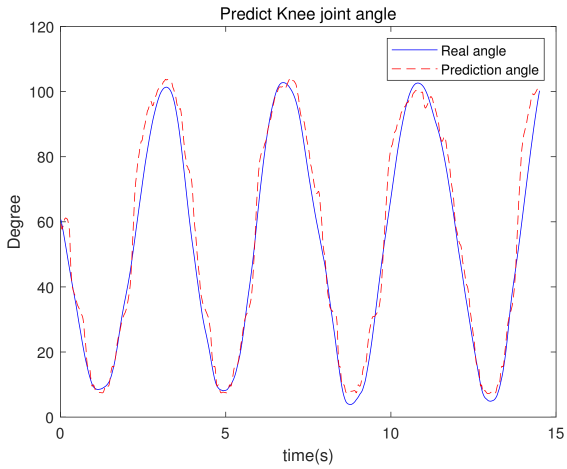

Fig. 7: The case where the C=69 and σ^2=0.04

Due to the sampling frequency of the sEMG signal becomes 100 Hz as the angle sensor, there are 3,200 pairs of muscle activation and joint angle data to be acquired. For the overall data, the first 1600 pairs is selected as the training data of the LS-SVM model, and the last 1450 pairs as the testing data. All experiments are simulated by MATLAB.

Because the LS-SVM model contains internal parameters C and σ^2, different parameter choices have different degrees of influence on the prediction effect of the model, as shown in Figure 6 and Figure 7. Figure 6 conveys the case where the parameters C=1 and σ^2=0.2, the root mean square error is 7.6936 after calculation. It can be seen from the figure that there is obvious shake, so this situation is not the best parameter choice. Figure 7 represents the case where the parameters C=69 and σ^2=0.04, the RMSE is 6.5302, the shake is significantly reduced, and the prediction effect is better.

Table 1: Calculating time

Algorithm	LS-SVM	LS-SVM-ZNN
Time	37s	12s

When the parameters are determined, the linear equations converted by LS-SVM are also determined. Faced with the problem of solving equations, the training time consumed by the traditional method of multiplying the inverse matrix and the proposed ZNN method was compared. The process can be expressed as Table 1. The consequences show that the calculating time consumed by ZNN to solve equations is only 12 seconds, which is significantly less than that based on the traditional method. At the same time, the feasibility of the proposed method is verified.

Table 2: Precision

Algorithm	LS-SVM-ZNN	BPNN
RMSE	6.5302	9.2680

So as to reflect the capability of the proposed scheme, the BPNN model is used as the comparative experiment with the same training data. The results are expressed in Figure 8.

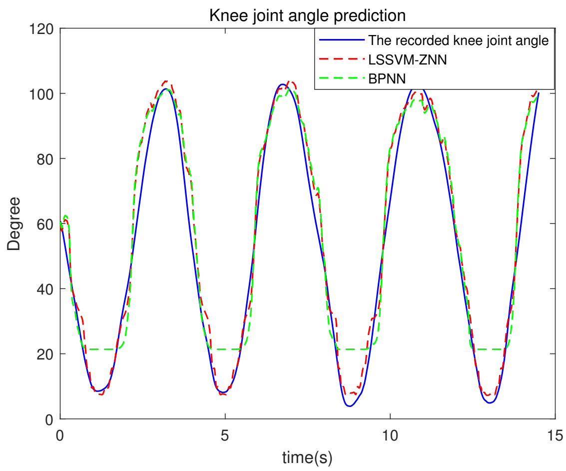

Fig. 8: Comparative Experiment

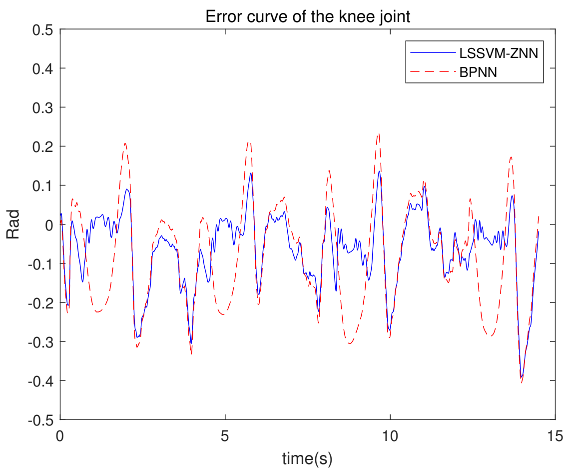

Fig. 9: Error curve

Because initial values of the weights between the neural network nodes are given randomly, even if the same training data is used, the results of each experiment are different. LS-SVM-ZNN is a more stable learning algorithm, and its result is only determined by the support vector. The RMSE of the two methods is shown in Table 2, and the error curve is shown in Figure 9. From the above results, the performance of the raised method in the paper is significantly better than BPNN. In addition, if the results of a healthy person's data learning are applied to another unhealthy person, then the two should have similar physical signs, so that the results will have more reference value.

5 Conclusions

In the paper, the raised proposal combined LS-SVM and ZNN was used to complete the prediction of the continuous motion of the knee joint. First, the sEMG signal containing human behavior information was obtained, and then performed a series of preprocessing on the signal. An exponential nonlinear formula was utilized to acquire the muscle activation of the corresponding muscle. Furthermore, the LS-SVM model was exploited to establish the regression equation of muscle activation and joint angle. The problem of quadratic programming was transformed into solving linear equations. The ZNN model was utilized to obtain the solution of the equations, and then the regression model was calculated. According to the results of comparison experiments, the proposed method has more stable and good performance, and the root mean square error is 6.5302, which was significantly smaller than the result calculated by BPNN. The result predicted by the model is applied as a reference input for controlling the robot, which has a powerful role in promoting the development of human-machine interaction.

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